



Babu 1-10-42
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REPLACEMENT SHEET

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FIG. 1

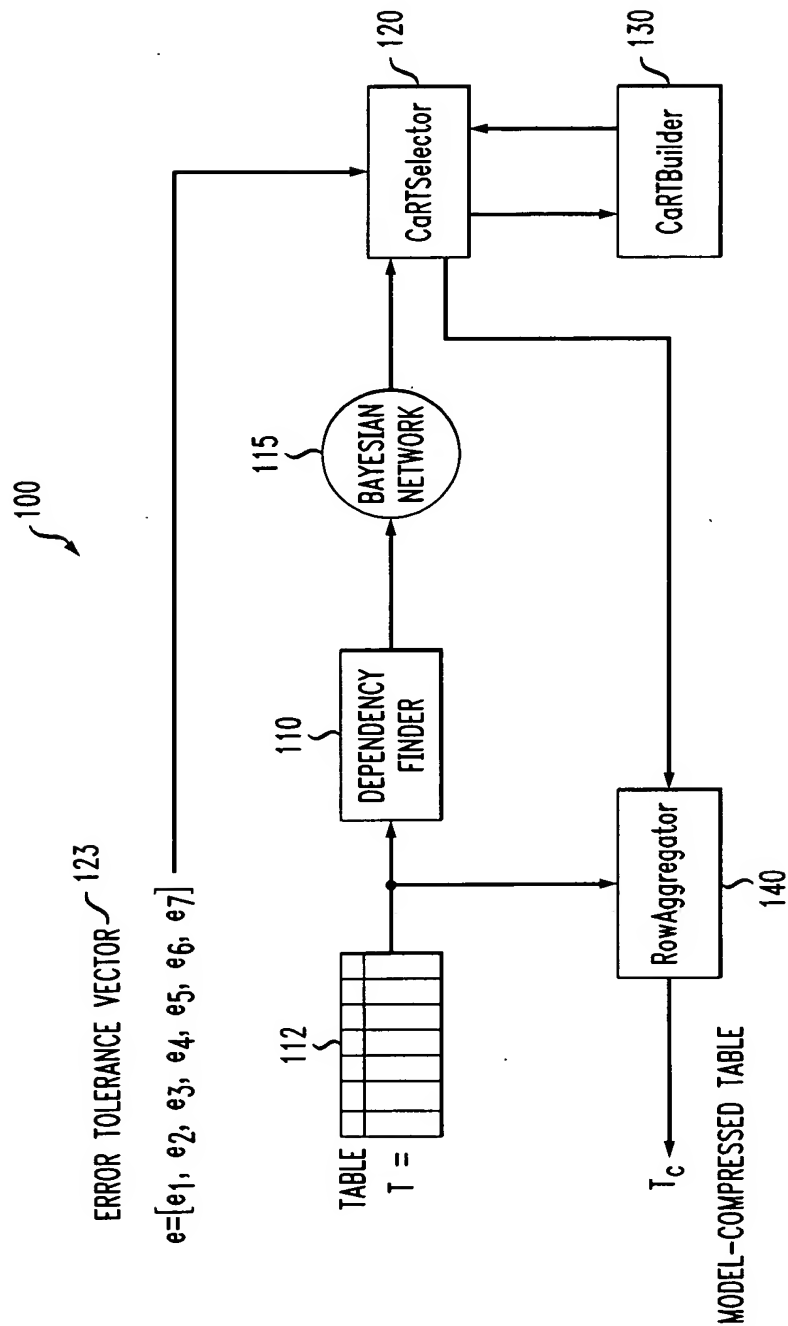


FIG. 2

The Greedy CaRT Selection Algorithm

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procedure Greedy (T(X) ,  $\bar{e}$ , G,  $\theta$ )
Input:  n-attribute table T and n-vector of error tolerances  $\bar{e}$ ;
        Bayesian network G on the set of attributes X and
        threshold  $\theta$  on the relative benefit for selecting a
        CaRT predictor.
Output: A set of materialized (predicted) attributes  $X_{mat}$  ( $X_{pred}$ 
        =  $X - X_{mat}$ ) and a CaRT predictor for each  $X_i \in X_{pred}$ .

begin
1.  $X_{mat} := X_{pred} := \Phi$ 
2. let  $\langle X_1, X_2, \dots, X_n \rangle$  be the attributes in X sorted in
   topological order of G
3. for i := 1, ..., n
4. if  $\Pi(X_i) = \Phi$  then  $X_{mat} := X_{mat} \cup \{X_i\}$  /*  $X_i$  must be
   materialized if it has no parents in G */
5. else
6.  $M := \text{BuildCaRT}(X_{mat} \rightarrow X_i, e_i)$ 
7. if  $(\text{MaterCost}(X_i) / \text{PredCost}(X_{mat} \rightarrow X_i)) > \theta$  then  $X_{pred} :=$ 
    $X_{pred} \cup \{X_i\}$ 
8. else  $X_{mat} := X_{mat} \cup \{X_i\}$ 
9. end
10. end
end
  
```

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FIG. 3A

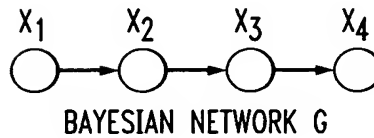


FIG. 3B

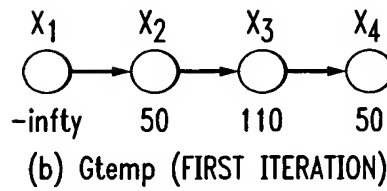


FIG. 3C

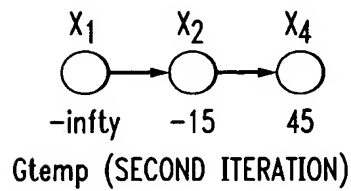


FIG. 3D

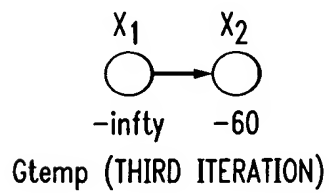


FIG. 4

The MaxIndependentSet CaRT Selection Algorithm

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procedure MaxIndependentSet (T(X) ,  $\bar{e}$ , G, neighborhood() )
Input:  n-attribute table T and n-vector of error tolerances  $\bar{e}$ ;
        Bayesian network G on the set of attributes X and function
        neighborhood () defining the "predictive neighborhood" of a
        node  $X_i$  in G (e.g.,  $\Pi(X_i)$  or  $\beta(X_i)$ ).
Output: A set of materialized (predicted) attributes  $X_{mat}$  ( $X_{pred} = X - X_{mat}$ )
        and a CaRT predictor  $PRED(X_i) \rightarrow X_i$  for each  $X_i \in X_{pred}$ .
begin
1.   $X_{mat} := X$ ,  $X_{pred} := \emptyset$ 
2.   $PRED(X_i) := \emptyset$  for all  $X_i \in X$ , improve := true
3.  while (improve  $\neq$  false) do
4.      for each  $X_i \in X_{mat}$ 
5.          mater_neighbors ( $X_i$ ) :=
              ( $X_{mat} \cap neighborhood(X_i)$ )  $\cup$  { $PRED(X) : X \in neighborhood(X_i), X \in X_{pred} - \{X_i\}$ }
6.           $M := BuildCaRT(Mater\_neighbors(X_i) \rightarrow X_i, e_i)$ 
7.          let  $PRED(X_i) \subseteq mater\_neighbors(X_i)$  be the set of
              predictor attributes used in M
8.          cost_changei := 0
9.          for each  $X_j \in X_{pred}$  such that  $X_i \in PRED(X_j)$ 
10.             NEW_PREDi ( $X_j$ ) :=  $PRED(X_j) - \{X_i\} \cup PRED(X_i)$ 
11.              $M := BuildCaRT(NEW\_PRED_i(X_j) \rightarrow X_j, e_j)$ 
12.             set NEW_PREDi ( $X_j$ ) to the (sub) set of
                  predictor attributes used in M
13.             cost_changei := cost_changei + (PredCost ( $PRED(X_j) \rightarrow X_j$ ) - PredCost (NEW_PREDi ( $X_j$ )  $\rightarrow X_j$ ))
14.         end
15.     end
    
```

FIG. 4 (cont)

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16. build an undirected, node-weighted graph  $G_{temp} = (X_{mat},$ 
     $E_{temp})$  on the current set of materialized
17. attributes  $X_{mat}$ , where:
18.     (a)  $E_{temp} := \{ (X,Y) : \text{for all pairs } X, Y \in X_{pred} \} \cup$ 
19.          $\{ (X_i, Y) : \text{for all } Y \in X_{mat} \}$ 
20.     (b)  $\text{weight}(X_i) := \text{MaterCost}(X_i) - \text{PredCost}(\text{PRED}(X_i)$ 
     $\rightarrow X_i) + \text{cost\_change}_i$  for each  $X_i \in X_{mat}$ 
21.  $S := \text{FindWMIS}(G_{temp})$  /* select (approximate) maximum
    weight independent set in  $G_{temp}$ 
22.                               as "maximum-benefit" subset of
    predicted attributes */
23. if ( $\sum_{X \in S} \text{weight}(X) \leq 0$ ) then improve := false
24. else /* update  $X_{mat}$ ,  $X_{pred}$ , and the chosen CaRT predictors */
25.   for each  $X_j \in X_{pred}$ 
26.     if ( $\text{PRED}(X_j) \cap S = \{X_i\}$ ) then  $\text{PRED}(X_j) :=$ 
     $\text{NEW\_PRED}_i(X_j)$ 
27.   end
28.    $X_{mat} := X_{mat} - S$ ,  $X_{pred} := X_{pred} \cup S$ 
29. end
30. end /* while */
end

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FIG. 5

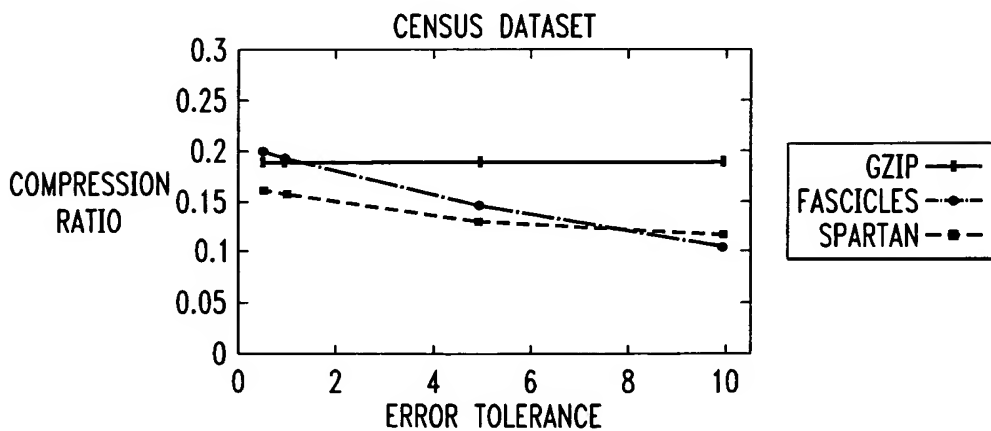
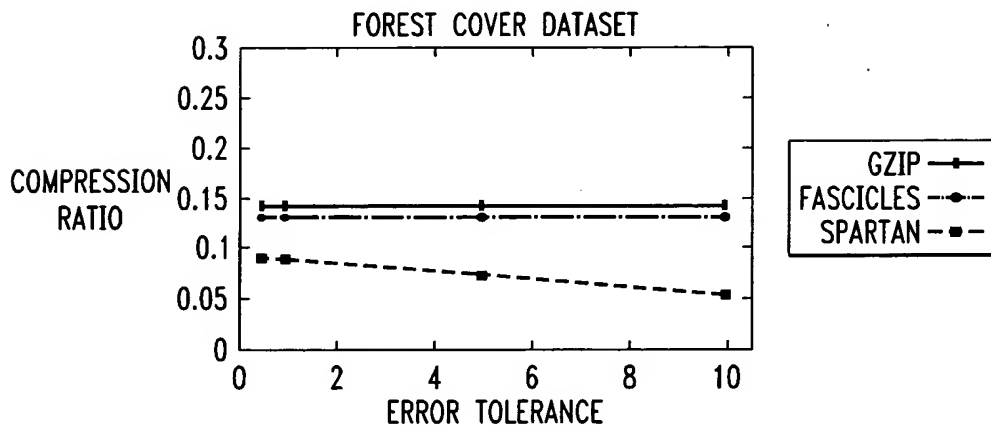
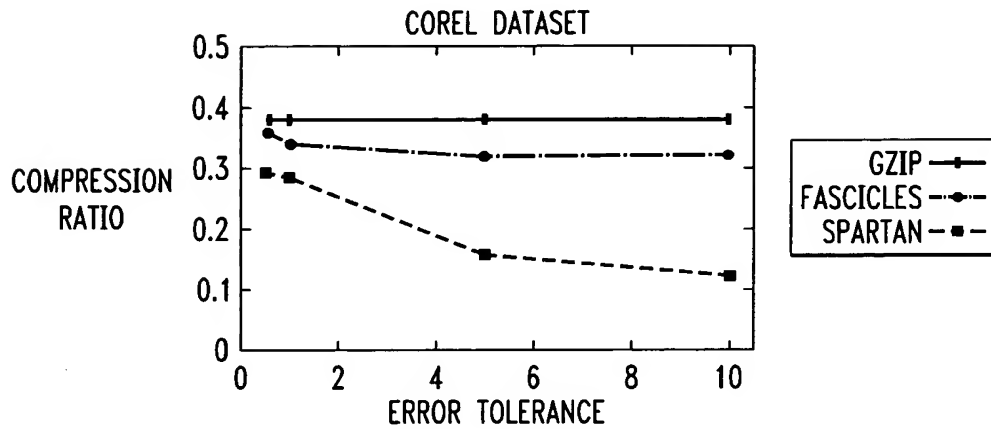
Algorithm for Estimating Lower Bound on Subtree Cost

```

procedure LowerBound (N, ei, b)
Input: Leaf N for which lower bound on subtree cost is to be
       computed; error tolerance ei for attribute Xi; bound b
       on the maximum number of internal nodes in subtree
       rooted at N.
Output: Lower bound L(N) on cost of subtree rooted at N.
begin
1.  for i := 1 to r
2.      minOut [i, 0] := i
3.  for J := 1 to b + 1
4.      minOut [0, j] := 0
5.  1 := 0
6.  for i := 1 to r
7.      while xi - x1+1 > 2 ei
8.          1 := 1 + 1
9.  for j := 1 to b + 1
10.     minOut [i, j] := min {minOut[i - 1, j] + 1, minOut [1, j-1]}
11. end
12. L(N) := ∞
13. for J := 0 to b
14.     L(N) := min {L(N), 2j + 1 + j log (|Xi|) + (j + 1 + minOut
        (r, j+1)) log (|dom(Xi)|)}
15. L(N) := min {L(N), 2b + 3 + (b + 1) log (|Xi|) + (b + 2) log
        (|dom(Xi)|)}
16. return L (N)
end
  
```

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FIG. 6



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FIG. 7A

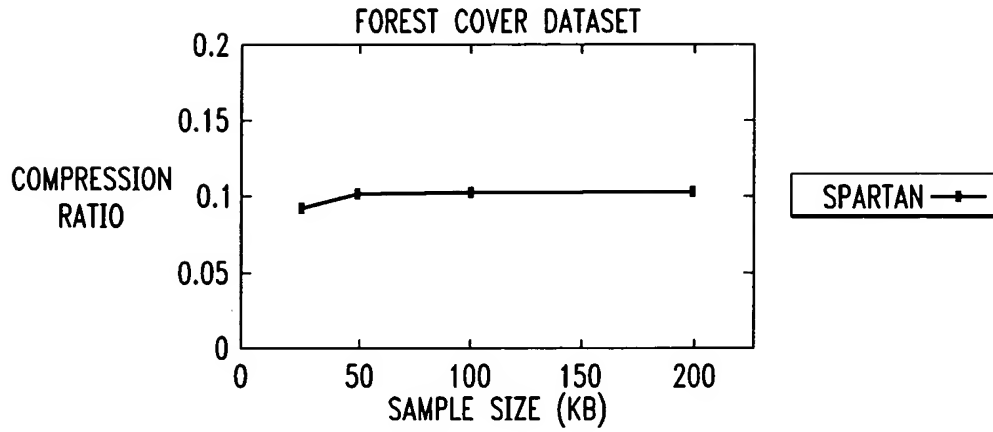


FIG. 7B

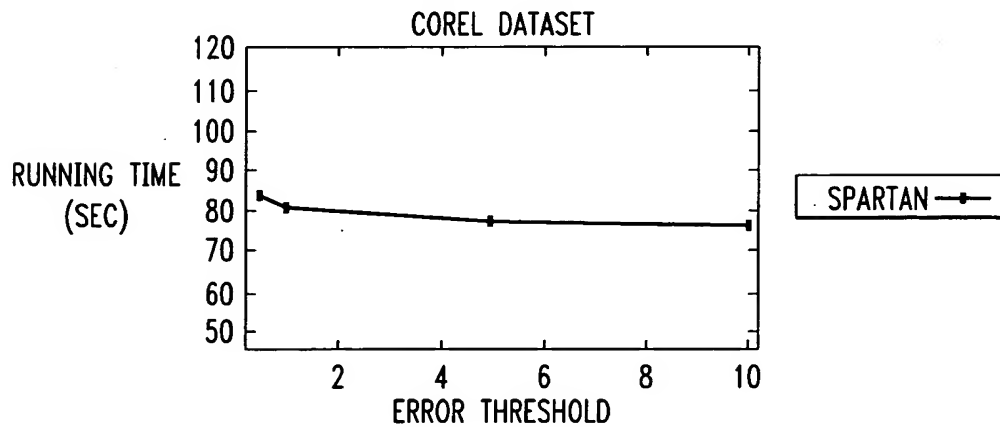


FIG. 7C

